How Are Illusory Objects Represented in Visual Working Memory?

Undergraduate Research Thesis

Presented in partial fulfillment of the requirements for graduation with Research Distinction in Neuroscience in the undergraduate colleges of The Ohio State University

by

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March 2020

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Acknowledgements

I would like to thank Dr. Andrew Leber and Dr. Ayala Allon for their support, guidance, and expertise during this project. A huge thank you goes to Jiageng Chen and Christopher Jones of the Vision & Cognitive Neuroscience Lab for their EEG know-how. I am eternally grateful to the Cognitive Control Lab's manager and research assistants for running participants and assisting with other details of the project: Molly McKinney, and Benjamin Dominguez, Katherine Friess, Kings Jiang, Vaibhav Khandelwal, Walden Li, Eric Reinhart, and Dana Shaw. Thank you to the graduate students of the Cognitive Control Lab, especially for their comments during the design stages of this project and while preparing for presentations: Heather Hansen, Yoolim Hong, and Paul Scotti. I am grateful to Dr. Ian Krajbich and Dr. Christopher Otter for serving on my thesis committee. Finally, I want to thank Lisa Heisterberg, a Medical Scientist Training Program student in the Cognitive Control Lab, for her ceaseless championing of this project and unwavering support.

Abstract

Visual Working Memory (VWM) is an online workspace that holds about 3-4 objects in an active state for a short period of time (Luck & Vogel, 1997). Individual differences in VWM capacity are related to fluid intelligence, problem solving, and other high-aptitude measures, and so are useful for predicting real world behaviors (Cowan et al., 2005; Unsworth, Fukuda, Awh, & Vogel 2014). One way people get around their capacity limitations is by grouping information into integrated units in VWM. Gestalt grouping cues, such as illusory objects, have been shown to improve performance on VWM tasks (Allon, Vixman, & Luria, 2019, Peterson, et al., 2015), but the question of how these improvements arise in the brain remains unanswered. Here, we asked whether the behavioral benefits derived from an illusory object (e.g., a Kanizsa triangle) result from a reduction in demands on VWM capacity. That is, are the objects which comprise the Kanizsa triangle represented in the brain as a single object, as three objects, or as something in between? We recorded EEG while subjects performed a bilateral change-detection task, with memory arrays configured in four conditions: 1 item, 3 items forming a Kanizsa triangle, 3 proximity grouped items, and 3 ungrouped items. We assessed the number of items held in VWM via the contralateral delay activity (CDA), an event-related potential component which represents the number of objects held in VWM. Replicating previous work, we saw a behavioral performance benefit for the Kanizsa triangle condition. However, the CDA amplitude for the Kanizsa condition was not different from either the proximity grouped objects condition or the ungrouped objects condition. This suggests that the behavioral benefits derived from the illusory object Kanizsa triangle are not a result of reduced storage demands in VWM. This may not be the final story, however. Future work will further delineate how illusory objects impact VWM.

keywords: contralateral delay activity, visual working memory, illusory objects

Motivation & Context

Visual Working Memory Capacity

Visual Working Memory (VWM) is an online workspace in the human brain which holds a limited amount of visual information in an active state for a short period of time. VWM requires that information is both acquired and represented visually (as opposed to, for example, verbally). These visual representations are actively maintained through sustained neural activity verifiable by physiological recordings rather than passively stored like long-term memories. Importantly, the *working* assignment means that VWM representations are important for the conduct of cognitive tasks (Luck & Vogel, 2013). However, most visual scenes in the real world have far more information than can be represented in VWM. This is because VWM is limited in capacity. Luck & Vogel (1997) found that VWM appears capable of holding only about 3-4 objects at a time. VWM appears not only limited in the number of objects that can be stored, but also in the resolution, or the number of details or features, of the stored objects (Alvarez & Cavanagh, 2004; Awh et al., 2007; Zhang & Luck, 2008). Thus, it appears that working memory can either hold few items with high fidelity or many items with lower fidelity (Brady et al., 2011).

Robust individual differences exist in VWM capacity (McNab & Klingberg, 2008; Vogel et al., 2005). For example, Fukuda and Vogel (2009) found that the ability to prevent attentional capture by salient but irrelevant stimuli is predicted by an individual’s working memory capacity. Individual differences like these relate to a variety of high-aptitude measures like fluid intelligence, verbal learning, and problem solving (Cowan et al., 2005; Cowan et al., 2006; Fukuda et al., 2010; Johnson et al., 2013; Unsworth et al., 2014). Higher capacity individuals tend to perform better on these measures than lower capacity individuals. VWM is thus important for guiding and influencing behavior. Because individual differences in VWM capacity are integral to the basic cognitive functions that underlie these measures, it is essential to understand the mechanisms by which VWM copes with its extreme capacity limitations.

Change Detection Tasks

Change detection tasks are commonly used to study VWM. For example, the 3-4 object VWM capacity was calculated from results in a change detection task. In a change detection task, participants are briefly shown a memory array of objects and are instructed to remember a feature, or a conjunction of features, of those objects. *Features* here are elements like color or orientation that contribute to the resolution of stored objects. Following a period of disappearance (retention interval), a test array appears, and subjects are asked to determine if the test array is the same or different as the memory array.

Grouping & Gestalt Cues

One possible mechanism to cope with our VWM capacity limitation is by grouping and parsing information into integrated units in VWM (Allon, Vixman, & Luria, 2019; Baylis & Driver, 1992; Li, Qian, & Liang, 2018; Wang, Weng, & He, 2012). Gestalt grouping is the idea that people will perceive some objects or elements in a visual array as “going together” more than others (Wagemans, et al, 2012). Several factors can influence whether an object is likely to be grouped with others. Some of these are: proximity (closeness of an object to another), similarity (sameness in color, size, and/or orientation), common fate (objects moving in the same way), symmetry (objects arranged in a symmetrical pattern in an array), parallelism (objects in corresponding locations), continuity (perceived as a single continuous object instead of as multiple objects), and closure (objects forming a closed figure) (see Wagemans et al., 2012 for a review). Several of these principles, including common region, connectedness, proximity, similarity, and closure, have been shown to produce VWM performance benefits (Woodman et al., 2003; Xu, 2002, 2006; Xu & Chun, 2006; Allon, Vixman, & Luria, 2019). These results demonstrate that it may not simply be a limit on the number of objects held in VWM; rather, the number of groups held may play a role. Gestalt principles like the above cut across multiple facets of perception and can determine what is perceived and how it is perceived in our environments.

The Gestalt principle of focus in this thesis is that of illusory contours. A Kanizsa triangle (Figure 1) is a salient global figure formed due to modal completion of an illusory triangle via local arrangements of Pac-Man shaped inducers. Previous findings demonstrate that items grouped together to form illusory contours improve performance on VWM tasks (Gao, et al, 2016; Peterson, et al., 2015; Allon, Vixman, & Luria, 2019).

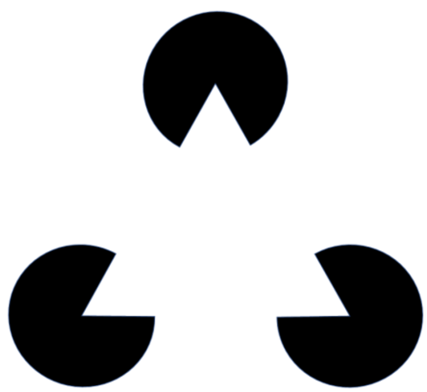

Figure 1: A Kanizsa triangle is composed of three "Pac-Man shapes". When properly oriented, these shapes form an illusory object, an object which appears to exist but does not really. This occurs because the area inside the illusory shape appears to be brighter than the background, though they are the same shade, causing the illusory object to appear to be an opaque surface superimposed on the objects which comprise it (Kanizsa, 1976).

The mechanisms that contribute to these VWM performance benefits are still an open question. There is evidence to suggest that illusory objects capture attention in a sequential process. Global aspects of stimuli, like the illusory shapes created by inducers, are preferentially processed compared to local stimuli attributes (Conci, et al., 2011). This preference for illusory objects is first evident in early visual processing (~75-190 ms post-stimulus appearance). There are larger amplitudes in early sensory components (N1, P1) for illusory object groupings vs. non-illusory groupings (Conci, et al., 2011). Then 200-300 ms post-stimulus appearance, there are enhanced N2pc amplitudes for Gestalt stimuli compared to non-Gestalt stimuli (Conci, et al., 2016) which indicates that Gestalt stimuli capture attention in a bottom-up fashion automatically. Thus, the Kanizsa illusory triangle would seem to first be bound into a coherent unit early in visual processing. Once this unit becomes available, attentional selection of the unit can take place. However, it is still unknown how these early visual and attentional processes affect how Kanizsa information is stored in VWM and in turn contribute to behavioral benefits.

Contralateral Delay Activity

While behavioral studies have aided in our understanding of the mechanisms of VWM, assessing a neural measure offers additional insights into how we deploy VWM to solve problems and operate in the world. The contralateral delay activity (CDA; See Figure 2) is an electroencephalographic (EEG) event-related potential measure, the amplitude of which increases as a function of the number of items currently being held in VWM. The CDA is calculated from posterior electrode sites by subtracting the ipsilateral hemifield activity from the contralateral hemifield stimulation. Because the CDA is calculated by subtracting the activity of one hemifield from another, it is essential to cue subjects to attend to one side of the screen or the other. It emerges at around 400 ms post-stimulus onset and is sustained for the duration of the VWM maintenance period. (Vogel & Machizawa, 2004; Luria, et al., 2016).

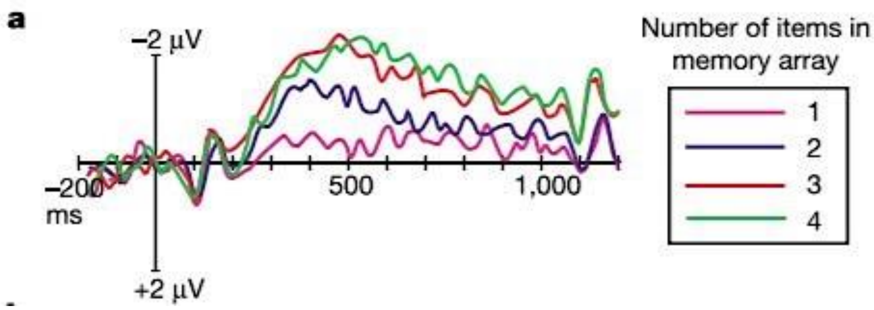

Figure 2: An example of the Contralateral Delay Activity (CDA) wave. X-axis: time. Y-axis: brain wave amplitudes of the CDA. The amplitude becomes higher as the number of objects in the array increases because the CDA amplitude increases according to how many items are held in VWM.
Figure adopted from Vogel & Machizawa (2004).

The advantage of using the CDA over other EEG components or behavioral measures is that it enables measurement of VWM capacity while also isolating this measurement from other processes involved, such as processing of low-level visual information (McCollough et al., 2007; Kang & Woodman, 2014) and processing of the number of spatial positions on the screen (Ikkai et al., 2010; Balaban & Luria, 2015). Also, because this is done using EEG, it has a high temporal resolution, making it a good tool to measure cognitive processes that evolve quickly over time—such as VWM. This component also asymptotes at a subject's behaviorally measured VWM capacity indicating that the CDA is sensitive to individual differences. The directness of the data provided by the CDA makes it better suited to the purposes of this project than behavioral measurements, such as reaction time and accuracy, alone.

Research Question & Significance

While previous studies have made use of grouped objects and illusory contours (Allon, Vixman, & Luria, 2018; Davis & Driver, 1994; Li, Qian, & Liang, 2018; Peterson et al, 2015; Wang, Weng, & He, 2018), and showed that there are behavioral performance benefits due to illusory contours, to the best of our knowledge none of them have made the necessary comparisons to conclusively understand how we represent illusory objects in VWM. Previous studies have found that grouping items via connectedness, common region, collinearity, and color produce lower activity as measured by ERP and fMRI than ungrouped stimuli (Gao et al., 2011; Xu & Chun 2006; Peterson et al., 2015). “Chunking,” or the ability to group information into integrated units in VWM, is another mechanism by which multiple objects may be reduced to a single object, meaning that only one object would be encoded. Thus, it may be that a Kanizsa triangle is indeed stored as fewer than three objects in VWM. However, given other studies failing to show grouping cues, such as similarity and proximity, leading to a modulated CDA amplitude (Shen et al., 2013; Morey et al., 2015), it is also possible for a Kanizsa triangle to be represented as three objects. Behavioral benefits seen previously could be the result of improved tagging of the inducers for encoding, or it could be due to overall enhanced object processing (Allon, Vixman, and Luria, 2019). Such enhanced processing could result in a higher resolution representation of three distinct objects inducers in VWM, leading to a behavioral benefit. Yet another possibility is for a Kanizsa triangle to be represented as less than three objects, but more than one object. This could possibly result if the illusory object improves the efficiency with which items are stored in VWM. Thus, a Kanizsa triangle could be represented as three distinct objects, as a single object, or perhaps something in between.

Knowing how we hold objects in VWM is key for understanding how VWM copes with its capacity limitations. This is important to address due to correlations between robust differences in VWM function and high aptitude measures, suggesting that working memory is a key mechanism for guiding our everyday behavior. Understanding how VWM works with its limitations will be integral for improving our performance in the cognitive tasks we engage in daily and can influence how we interact with the world, learn, and organize information.

Looking at individual differences in the human ability to cope can inform interventions for the future.

In this study, subjects were tasked with remembering the orientation of pac-man stimuli in a change detection task. The task was configured in four conditions: a single object condition, a Kanizsa triangle condition, a three object proximity grouped condition, and an ungrouped condition. If a Kanizsa triangle condition were represented as a single object, its CDA amplitude would be similar to the CDA amplitude of a single object condition. If it were represented as three objects, its CDA amplitude would be represented similarly to other three object conditions. If the Kanizsa triangle reduced requirements on VWM capacity but was still represented as more than one object (e.g., as the triangle plus one of the inducers), then its CDA amplitude could be between that of a single object condition and a three object condition. Behaviorally, we expected to replicate previous findings that show the Kanizsa triangle improves VWM performance accuracy (Allon, Vixman, and Luria, 2019). Through this task, the question of how illusory objects are represented in VWM was assessed.

Methods

Participants

Thirty-one people (M 21 years, SD 2.6, 13 men, 17 women, 1 transgender/nonbinary, gender collected by open self-report) participated in one behavioral task and one EEG experimental task conducted within the same session. Each session took approximately three hours, with the experiment itself taking approximately 1.5 hours, plus an additional 1.5 hours of preparation time. Participants were paid $15 per hour. Participants gave their informed consent to the protocol approved by the IRB at The Ohio State University. Each participant had normal or corrected-to-normal visual acuity and self-reported normal color vision. Eleven participants were excluded from the experimental data analysis due to greater than 25% of trials rejected because of eyeblinks or eye movements during the EEG study. One additional participant was excluded due to having a negative value for the VWM capacity estimate K.

Apparatus

The experiment was presented on 21-inch BenQ XL2420T monitor with a 120 Hz refresh rate using 1920 x 1080 resolution graphics mode. Participants were approximately 65 cm from the monitor for the duration of the experiment.

Stimuli and Procedure

Preliminary Task

Prior to the EEG task, we separately assessed participants' VWM capacity using a color change detection task (Fukuda & Vogel, 2009; Luck & Vogel, 1997; Vogel et al., 2001) (Figure 3) that consisted of 2 blocks of 60 trials. We verbally and textually explained the task and participants completed 10 practice trials prior to beginning. Trials began with a fixation cross (visual angle 0.53 x 0.53 degrees) presented for 1000 ms. Then, memory arrays of 4 or 8 squares were displayed for 150 ms. Following a retention period of 900 ms, participants were presented with a test square and asked to determine if the color of the item was the same or different than it was in the memory array. Participants were required to make an un-speeded response by pressing Z or / on the keyboard (for same or different), counterbalanced across the participants, before continuing to the next trial. On different trials, the color of the object was replaced with a color not in the memory array.

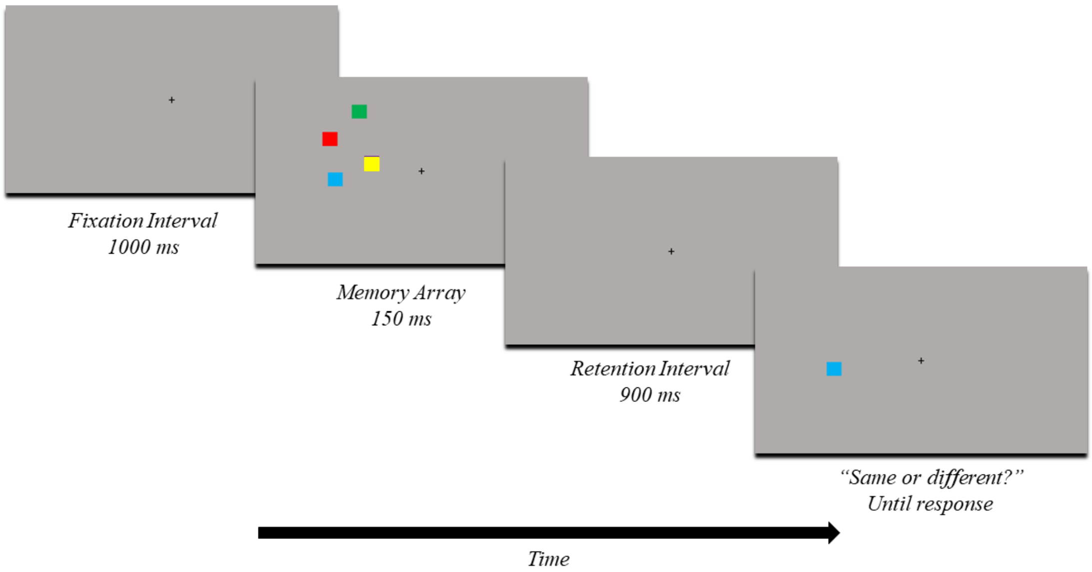

Figure 3: Change Detection Trial

The visual angle of each square was 1.4 x 1.4 degrees. All stimuli were randomly positioned within a region subtending 14.61 x 14.61 degree visual angle on a black background. The color of the squares was randomized from a set of nine colors (red (255, 0, 0), green (0, 255, 0), blue (0, 0, 255), yellow (255, 255, 0), magenta (255, 0, 255), cyan (0, 255, 255), white (255, 255, 255), black (0, 0, 0), orange (255, 128, 0)), and no two squares in an array were the same color.

The accuracy of each individual participant was used to calculate a K value for both set sizes, using the equation $K = S \times (H - F)$, where K is memory capacity, S is the size of the memory array, H is the observed hit rate, and F is the false alarm rate (Cowan, 2001; Pashler, 1988). The average of the values for each set size was used to estimate the participant's K value.

Experimental Task

Before the task began, participants were prepared via verbal and textual instructions and sixteen practice trials. During the study (Figure 4), participants completed 18 blocks of 56 trials each, for a total of 1008 trials, of a change-detection task (Luck & Vogel, 1997; Vogel & Machizawa, 2004). After a fixation period of 200 ms (visual angle of fixation cross: 0.44 degrees x 0.44 degrees), participants were cued with arrows (visual angle: 1.85 degrees x 0.44 degrees) to the relevant side for 400 ms. Then, participants were presented (SOA: 300, 400, or 500 ms) with an array of colored circles with notches cut out of their circumference and asked to remember the orientation of these shapes (i.e., which direction the notch of the shape was pointing) for 200 ms. After a retention period of 900 ms, a test item appeared, and participants made an un-speeded response using the keyboard, indicating whether the item had the same or different orientation relative to the memory array item (Allon & Luria, 2019). "Different" trials had an orientation difference of at least 40 degrees from the memory array object. Memory arrays were configured in four conditions: single item (SO), three Kanizsa grouped items (3K), three proximity grouped items (3G), three ungrouped items (3U). Conditions were inter-mixed within blocks at random. The same number of trials per condition were shown in each block.

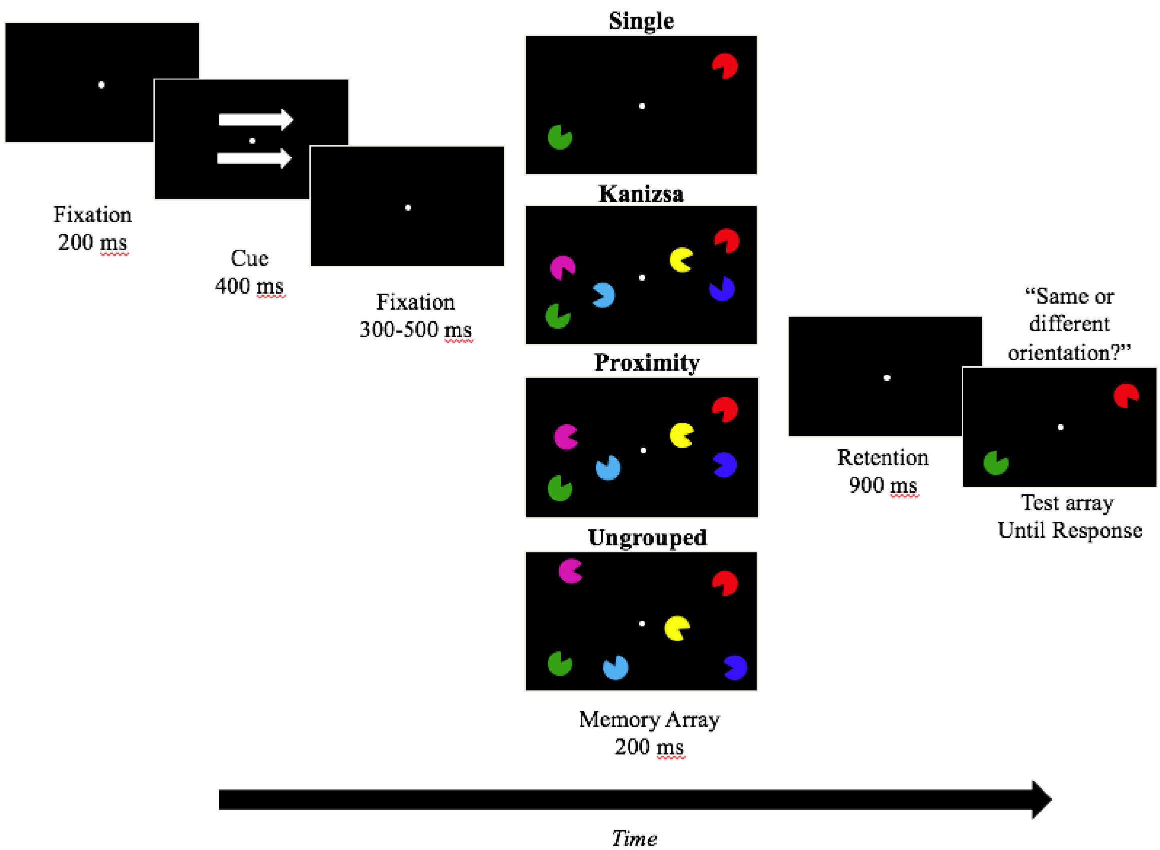

Figure 4: Experimental trial.

The radius of the stimuli was 0.75 degrees visual angle, and the visual angle of the Kanizsa triangle illusory object was approximately 3.44 degrees. All stimuli were randomly positioned within a 15.07 x 15.07 degrees visual angle region on the monitor on a black background. The color of the squares was randomized from a pool of eight colors (red (255 0 0), dark green (0 104 76), blue (0 0 255), yellow (255 255 0), pink (255 0 255), cyan (0 255 255), green (0 255 0), brown (102 51 0)); no two items in an array were the same color.

Electroencephalography recordings

We recorded EEG in an electromagnetically shielded room with a BrainVision EEG recording system (BrainProducts GmbH, Munich, Germany). Data were recorded from 32 scalp electrodes predominantly at occipital and parietal sites because that is where the CDA is most pronounced: Fp1, Fp2, AF3, AF4, F3, F4, F7, F8, Fz, FCz, C3, C4, Cz, T7, T8, P1, P2, P3, P4, P5, P6, P7, P8, Pz, PO3, PO4, PO7, PO8, POz, O1, O2, and Oz. The horizontal electrooculogram (EOG) was recorded from face electrodes placed approximately 1 cm to the left and right of the external canthi to detect horizontal eye movements. Vertical EOG was recorded from electrodes below the left eye and above and below the right eye to detect vertical eye movements, including eye blinks.

Signal processing and analysis were performed using EEGLAB Toolbox (Delorme & Makeig, 2004), ERPLAB Toolbox (Lopez-Caleron & Luck, 2014), and MATLAB (The Mathworks, Inc.). All electrodes were referenced offline to the average of the left and right mastoid electrodes. We segmented continuous data into epochs from -200 to +1,100 ms relative to onset of the memory array for analysis of the CDA component. Data were normalized to a 200 ms window before the onset of the memory array. Artifact detection was performed using a peak-to-peak analysis based on a sliding window of 200 ms wide with a step of 100 ms. Threshold activity for rejecting trials was adjusted for each participant and was either 75 or 85 mV at the EOG electrodes and 100 or 120 mV at the analyzed electrodes (P7, P8, PO8, PO3, and PO4). This procedure resulted in a mean rejection rate of 10.41%. Subjects that had greater than 25% of their data rejected at the highest thresholds were excluded. The epoched data were then averaged and low-pass filtered using a noncausal Butterworth filter (12 dB/oct) with a half-amplitude cutoff at 30 Hz. Only correct trials with reaction times higher than 100 ms or lower than 3,000 ms were included in the analysis.

CDA Analysis

The CDA was measured for each of the conditions (SO, 3K, 3G, 3U) as the difference in mean amplitude between the ipsilateral and contralateral waveforms recorded at the analyzed electrodes (PO7/PO8, P7/P8, PO3/PO4) from 400-1,000 ms after the onset of the memory array. False discovery rate was controlled during multiple comparisons using a Holm-Bonferroni correction (Holm, 1979). P-values denoted by p_{HB}.

Behavioral Analysis of EEG Task

Trials with RTs lower than 100 ms or higher than 3,000 ms would have been removed from analysis, however no trials met these criteria. Data preparation was conducted via custom MATLAB and SPSS scripts. False discovery rate was controlled during multiple comparisons using a Holm-Bonferroni correction (Holm, 1979), P-values denoted by p_{HB}.

Results

Behavioral Results

Accuracy rates were analyzed using a repeated-measures analysis of variance (ANOVA) with condition (SO, 3K, 3G, 3U) as the within-subject independent variable. Mauchly's test indicated the assumption of sphericity was violated ($\chi^2(5) = 18.517$, $p = .002$, $\varepsilon = .584$) thus a Greenhouse-Geisser correction was applied. The ANOVA revealed that there was a significant difference in accuracy between our conditions ($F(1.751, 31.513) = 121.519$, $p_{HB} = < .001$). There was significantly better accuracy for the SO condition versus the 3K ($t(18) = 7.482$, $p_{HB} < .001$), 3G ($t(18) = 20.154$, $p_{HB} < .001$), and 3U ($t(18) = 26.607$, $p_{HB} = <.001$) conditions. There was also significantly better accuracy for the 3K condition than for the 3G ($t(18) = 6.185$, $p_{HB} < .001$) and 3U ($t(18) = 5.121$, $p_{HB} < .001$) conditions. There were no other significant differences in accuracy. These behavioral results replicate the results of Allon, Vixman, and Luria, 2019: the Kanizsa triangle condition provides a behavioral benefit in terms of accuracy.

Reaction times were analyzed using a repeated-measures analysis of variance (ANOVA) with condition (SO, 3K, 3G, 3U) as the within-subject independent variable. Mauchly's test of sphericity was violated ($\chi^2(5) = 22.814$, $p < .001$, $\varepsilon = .529$), so we used a Greenhouse-Geisser correction. The ANOVA revealed that there was a significant difference in response time between conditions ($F(1.587, 28.564) = 83.22$, $p = < .001$). Subjects were significantly faster in the SO condition versus the 3K ($t(18) = -13.281$, $p_{HB} = < .001$), 3G ($t(18) = -10.256$, $p_{HB} = < .001$), and 3U ($t(18) = -9.600$, $p_{HB} = < .001$) conditions, There were no other significant differences in RT between conditions.

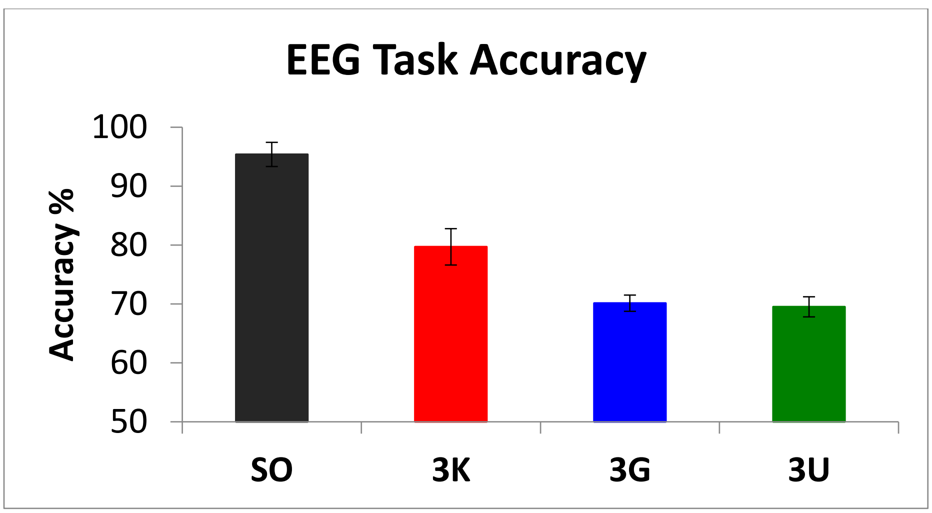

Figure 5: Percent accurate for each condition: single object (SO), 3 objects in a Kanizsa triangle (3K), 3 proximity grouped objects (3G), 3 ungrouped objects (3U).. Numerical data in Table 1. Error bars depict the within subject 95% confidence interval calculated using the Cousineau method (Cousineau, 2005) with a Morey correction (Morey, 2008)

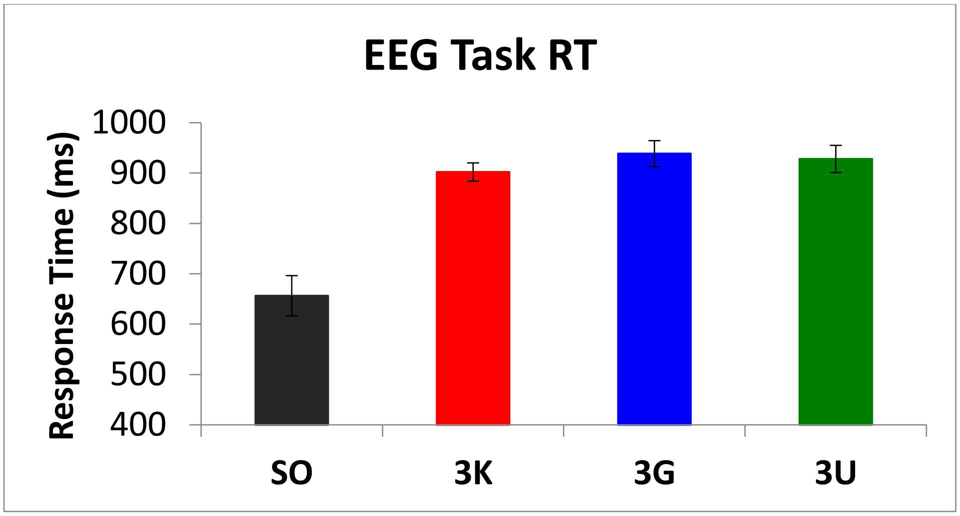

Figure 6: Reaction time for each condition. Numerical data in Table 1. Error bars depict the within subject 95% confidence interval calculated using the Cousineau method (Cousineau, 2005) with a Morey correction (Morey, 2008) .

Table 1: Accuracy and Response time averages and standard deviations

Condition	**SO**	**3K**	**3G**	**3U**
Accuracy (mean, SD)	95.4%, 3.9%	79.7%, 10.5%	69.8%, 7.4%	69.3%, 6.1%
Response time (mean, SD)	656.3ms, 160.8ms	902.1ms, 211.5ms	938.6ms, 235.8ms	928.0ms, 240.8ms

VWM Capacity Estimate (K): Change-detection task

The mean VWM capacity was 2.37 (SD = 0.73) with a range from 0.53 to 3.16.

Correlations between K and Accuracy & Response Time

To assess for the impact of VWM capacity on behavioral performance, K was correlated with accuracy and RT. Subjects with a higher VWM capacity were significantly more accurate at the Kanizsa condition, $r(17) = .57$, $p_{HB} = .010$. Subjects with higher VWM capacity were marginally more accurate on the 3 grouped object condition, $r(17) = .44$, $p_{HB} = .057$. None of the correlations between K and response time reached significance. See table 2 for all correlations.

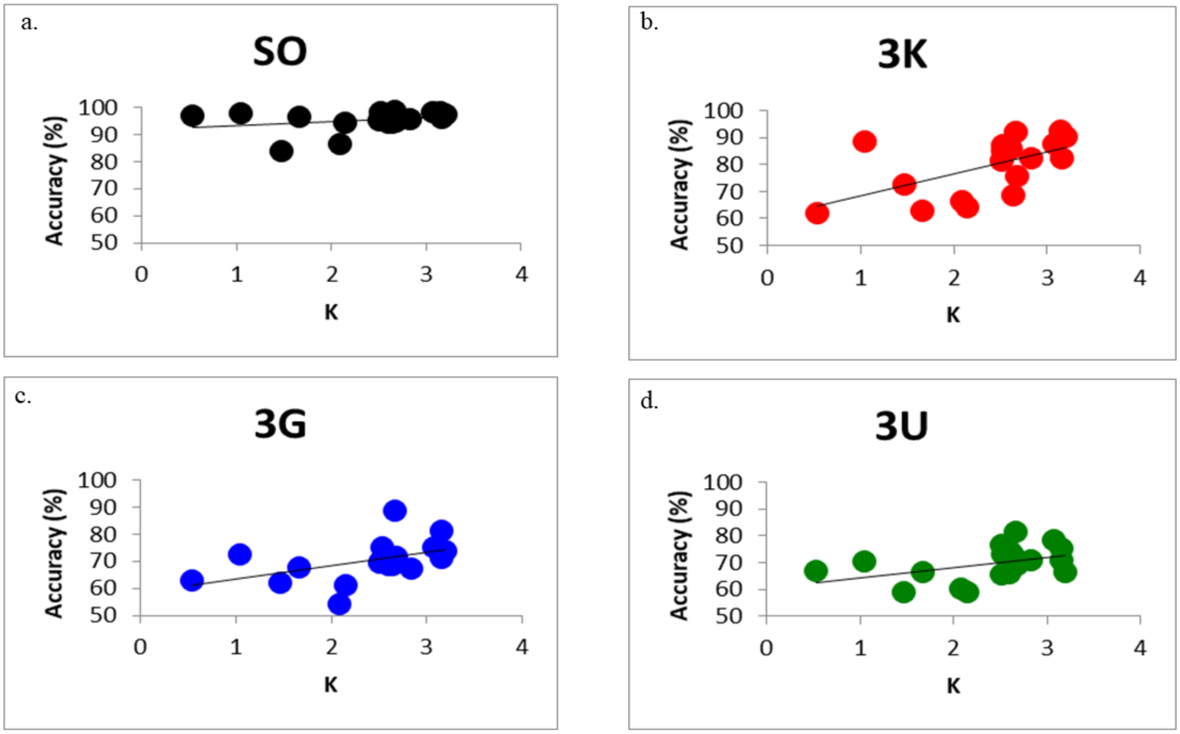

Figure 7: Scatter plots of K correlations with accuracy by condition.

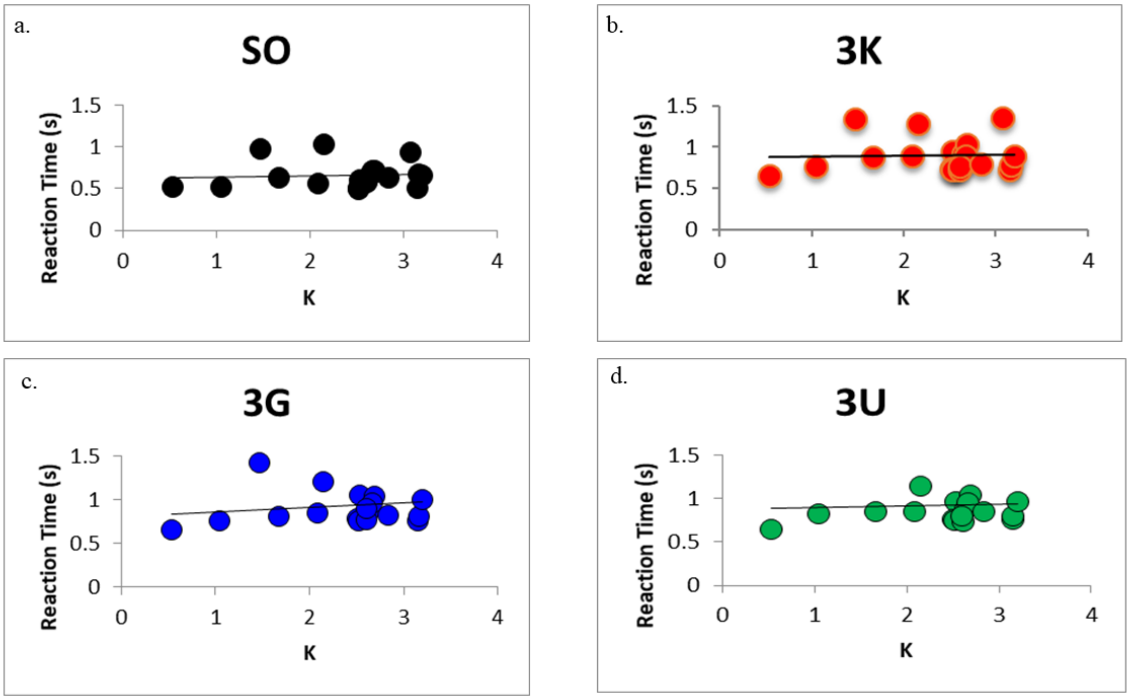

Figure8, a-d: Scatter plots of K correlations with reaction time by condition.

Table 2: Correlations between K & accuracy and K & response time for each condition

Condition	**SO**	**3K**	**3G**	**3U**
Accuracy r [95% CI]	.29 [-.13 .78]	.57 [.09 .86] *	.44 [.2 .73] #	.38 [.09 .65]
Response time r [95% CI]	.05 [-.53 .52]	.05 [-.55 .48]	.17 [-.47 .58]	.07 [-.63 .54]

*** = p < .05 , # = p < .1 (Holm-Bonferroni corrected)**

CDA Results

The CDA waveforms are presented in Figure 5. To assess for differences in CDA amplitude across conditions, a repeated measures ANOVA with condition (SO, 3K, 3G, 3U) as the within-subject independent variables was conducted. Mauchly's test of sphericity was not violated. The ANOVA revealed that there was a significant difference in CDA amplitude between conditions ($F(3, 54) = 13.034$, $p = < .001$). There was a significantly lower CDA amplitude for the SO waveform than for the 3K ($t(18) = 5.725$, $pHB = < .001$), 3G ($t(18) = 4.537$, $pHB = .001$), and 3U ($t(18) = 4.766$, $pHB < .001$) conditions. We did not find that the Kanzisa condition reduced CDA amplitude; it was statistically no different than the 3 grouped and 3 ungrouped conditions. No other significant differences were found.

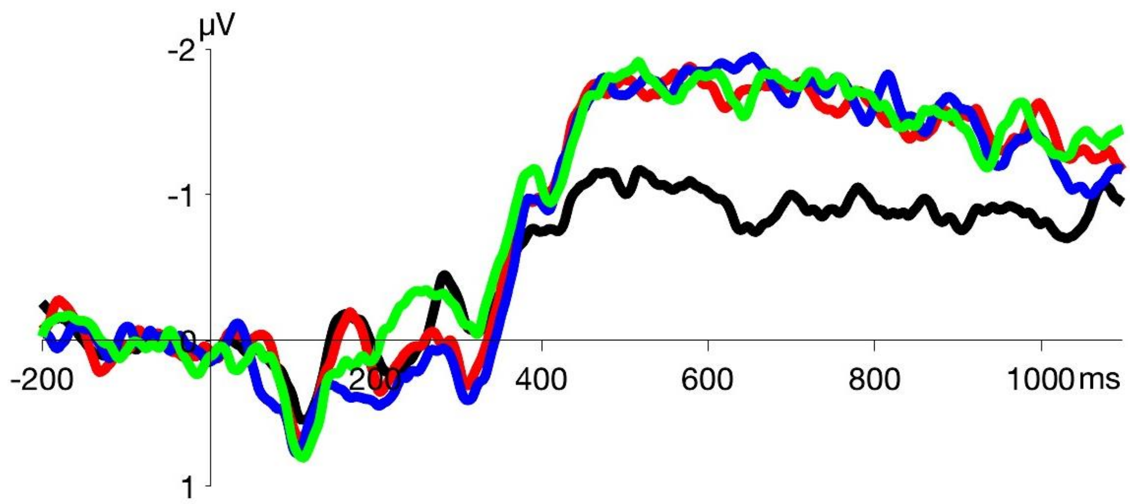

Figure 11: CDA waveform. Analysis window from 400-1000ms. CDA averaged across P7/P8, PO3/PO4, and PO7/PO8. Black: SO, Red: 3K, Blue: 3G, Green: 3U.

Correlations between K and CDA Amplitude

To assess for the impact of VWM capacity on CDA amplitude, K was correlated with CDA amplitude for each condition. None of the correlations reached significance. See table 3 for all correlations.

Table 3: Correlations between K CDA amplitude for each condition

Condition	**SO**	**3K**	**3G**	**3U**
Accuracy r [95% CI]	-.18 [-.48 .23]	.57 [.09 .86]	.44 [.2 .73]	.38 [.09 .65]
*** = p < .05, # = p < .1 uncorrected**				

Discussion

The goal of this study was to examine the question of how illusory objects, specifically the illusory object Kanizsa triangle, is represented in visual working memory. Previous studies (e.g. Gao et al., 2016; Peterson & Berryhill, 2013) demonstrated that Gestalt grouping cues like the Kanizsa triangle can improve accuracy in VWM tasks.

In this experiment, participants performed a change-detection task that included four trial conditions: single object (SO), three objects arranged in a Kanizsa triangle (3K), three objects grouped by proximity (3G), and three ungrouped objects (3U). Orientation was used as the test feature due to its task relevance. We measured the contralateral delay activity event-related potential waveform while participants completed the task. The results indicated that, while the Kanizsa triangle has a clear behavioral benefit for this task, CDA amplitude did not decrease during the 3K condition. Despite the relative strength of the illusory object as a Gestalt grouping cue (Kimchi et al., 2007), it does not appear to modulate the representation of its inducers in VWM. That is, the Kanizsa triangle appears to be represented as three objects in the brain.

The above results were surprising in light of other research. For example, Peterson et al. (2015) found that behavioral benefits to VWM were always accompanied by a reduction in CDA amplitude for arrays utilizing the Gestalt principles of similarity, proximity, and uniform connectedness. Additionally, unpublished results from McCollough 2011's doctoral dissertation found a reduction in CDA amplitude as well as a behavioral benefit when participants performed an orientation change-detection task using a Kanizsa triangle. These results would suggest that we should have seen a reduction in CDA amplitude because we saw behavioral benefits for the Kanizsa triangle illusory object condition. However, no such reduction in CDA amplitude was seen. Our results cannot corroborate those found in McCollough (2011).

Why did we not see a reduction in CDA amplitude? One hypothesis might be that the illusory object was not salient enough. It is possible that making the illusory object inducers all the same color would have boosted object salience by improving the contrast and allowing stronger perception of the illusory triangle (Spehar, 2000; Spehar & Clifford, 2003). This may have permitted stronger capture of the triangle and inducers as a single object. Modulating this, however, would not necessarily help us explain why we still see the behavioral benefit despite the salience of the illusory object not being as great as theoretically possible. Another hypothesis is that the behavioral benefit comes not from the representation of the object in VWM but instead from further processing at other levels. Perhaps participants were engaging their long-term memory or using some form of verbal rehearsal to better remember the orientation of the shapes in the Kanizsa condition. However, if there was additional processing occurring, we would expect to see a difference in reaction time between the Kanizsa condition and the other three object conditions: additional processing should take more time. This is unlikely also because the change detection paradigm has been shown to be minimally influenced by long-term memory and verbal working memory when the retention interval and encoding time are of a short duration (Cowan, 2001), as was used in our study. Due to not seeing significant differences in reaction time between the Kanizsa condition and the 3 grouped and 3 ungrouped object conditions, this possibility does not seem likely.

The results currently seem to be most explained by participants not having enough time to efficiently pick up and utilize the triangle to influence the encoding of visual information. When debriefing subjects, several participants voluntarily reported that they noticed the Kanizsa triangle during the experiment. A few subjects also commented noticing the triangle but being unable to do anything with that information during the trial. Thus, it is possible that it takes more time than the allotted 200 ms to become attentionally aware of and implement an attentional encoding strategy that utilizes the Kanizsa triangle. Due to the lack of time, subjects may have been unable to employ a more efficient encoding strategy or chunk items effectively. This may explain why we did not see an effect of the illusory triangle on CDA amplitude. Studies have shown that the encoding strategy subjects utilize during change detection tasks plays a role in performance, VWM capacity, and CDA amplitude. For example, Bengson & Luck, 2016, instructed subjects to adopt different strategies in a change detection task (e.g. remember entire display, focus on subset of items, just “do your best”). Performance was best in subjects told to remember everything even though the set size of displays was beyond their storage capacity. In Linke, et al., 2011, it was found that subjects with lower IQ or low capacity adopt a non-optimal attentional strategy during encoding which results in poorer performance. When provided with helpful grouping information, performance improved. Rabbitt, et al., 2017, demonstrated that CDA amplitude can be modulated when participants were instructed to group items to form a constellation rather than encode individual item locations. These three examples exemplify the key effect of encoding strategy on VWM. For encoding strategy to play a role in our study, the Kanizsa triangle would have to be attentionally selected. However, since it takes at least 150 ms for the brain to differentiate illusory objects from non-illusory object stimuli, and at least 220 ms for a bottom-up attentional signal to arise (Marini & Marzi, 2016), it is not probable that a 200 ms memory array even with a 900 ms retention interval would provide the duration necessary for adoption of an efficient encoding strategy. Additionally, the duration of WM encoding increases proportionally to increasing object complexity. Single feature objects take only about 50 ms to encode (Vogel, Woodman, Luck, 2006), whereas more complex objects like faces take about 500 ms (Curby & Gauthier, 2007). The Kanizsa complexity seems somewhere in between a single feature object and face stimuli. Because of the short duration of the memory array and the fact that there was a behavioral benefit for the Kanizsa condition, perhaps the participants were storing the triangle and as many inducers as possible until they filled all slots in VWM. Rather than a more efficient way of storing information, subjects had to store as much information as they could in the limited time provided.

McCollough (2011) found a reduction in CDA amplitude using a longer memory array time, 500 ms. When these results are taken in the context of the literature which suggests the importance of encoding time for efficient implementation of an encoding strategy, it seems increasingly plausible that our study rendered no decrease in CDA amplitude because of inadequate encoding time. The McCollough 2011 results can bolster our confidence in the pursuit of this direction. Our future work will explore what happens when participants are given more time with the memory array. Will people be better able to efficiently pick up the Kanizsa triangle, ignoring the inducers? From our results, we saw a significant correlation between VWM capacity and accuracy for the Kanizsa condition. Even with only 200 ms encoding time, high VWM capacity individuals are able to derive more of a behavioral benefit from the Kanizsa triangle, despite not having a reduced CDA amplitude. With increased encoding time, it is possible that these higher VWM capacity individuals will exhibit reduced CDA amplitudes, and perhaps lower VWM capacity subjects will be able to derive greater behavioral benefits than they did during the experiment with a shorter encoding time.

Conclusion

How is the Kanizsa triangle represented in visual working memory? At this time, our results imply that the triangle is represented as three objects in VWM. This does not account for the behavioral benefit we and others have observed when the Kanizsa triangle is deployed, nor does it corroborate previous research, which suggests that Gestalt grouping cues should create a reduction in CDA amplitude. Future work will attempt to modulate efficiency of participants' encoding strategies by increasing the interval of the memory array.

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